A Review of

**"REVIEW OF METHODS, PROGRESS AND CROSS-VALIDATION STUDIES
PERTAINING TO POPULATION TREND AND RISK ASSESSMENT FOR
COLUMBIA RIVER SALMONIDS"**
By E.E. Holmes (November 2003)

General Comments:

A review of methods that assess annual population growth rates was recognized as
necessary by the federal consultative parties for the 2000 Biological Opinion (BO) for the
Federal Columbia River Power System (FCRPS). The need for such a review was, in a
sense, confirmed through the recent judicial remand of the same BO. In both forums, the
NorthWest Fisheries Science Center (NWFSC) was requested to "review related methods
of characterizing population trends, especially those that had been suggested as
alternatives to 'lambda' estimation" in comments on both the BO and the litigation. The
white paper purports to conduct such a review and does indeed discuss methods for
estimating population trends and extinction risks. It summarizes recent work published
by Holmes and others in the peer-reviewed scientific literature. What it does not do,
however, is discuss alternatives to lambda estimations. Instead, it establishes the
credentials of the extensive work done over the last three years to validate the diffusion
approximation model for salmonid population data.

Extinction risk is evaluated based on current estimates of population size, trend, and
variability. The 2000 Biological Opinion jeopardy analysis focused on probability of
extinction and probability of recovery as the critical metrics, not lambda *per se*. The
reviewers should comment in detail on the strengths and weaknesses of using 100-year
extinction probability in the jeopardy analysis as opposed to a more reliable, but data
quality or assumption dependent, measure such as lambda. They could also evaluate the
accuracy of their favored population viability analyses in predicting the status of wild
populations 100 years into the future. Holmes (2001) argues for using lambda as a risk
measure because reliance on a risk metric with recalcitrant estimation problems
(extinction risk) is hard to justify when an equally useful and more reliable measure is
available.

Coulson et al. (2001) pointed out the many pitfalls in population viability analysis. They
argue that "population viability analyses can only be accurate at predicting extinction
probabilities if data are extensive and reliable, and if distribution of vital rates between
individuals and years can be assumed to be stationary in the future, or if any changes can
be accurately predicted." Salmon populations are known to undergo large nonstationary
changes in vital rates due to ocean/climate regime shifts and changes in harvest rates.
These are not well treated in the current CRI analysis because it assumes a stationary
process.

Extinction, under the population viability analysis model, can only come about as the result of long-term, gradual declines (e.g., birth rate < replacement rate over many years, as in Italy or Germany). In fact, it appears that most extinctions are the result of catastrophes that are not well-predicted by Population Viability Analysis methods. For salmon stocks in question, the only recent (past several decades years), well-documented extinctions have occurred due to stocks' exclusion from large spawning areas (upper Clearwater, above Grand Coulee and above Hells Canyon), and from deliberate poisoning with rotenone (of sockeye in Idaho lakes). None of these would have been predicted by Population Viability Analysis methods alone.

A possible conclusion to be drawn: either do not try to predict extinction, or place very large caveats around any such predictions.

Proposal:

Later in these comments, we offer some suggestions for strengthening and/or modifying the basic approach now used, as well as make a few suggestions of new techniques. In the meantime, we would like to propose a more thorough review be performed in response to the present circumstances of a judicially remanded Biological Opinion..

A thorough review of methods should include establishing a set of criteria against which the assessment of alternative methods can be objectively evaluated. These criteria were not provided. The author's and other assessment methods were evaluated in the paper using limited criteria applied inconsistently. An objective review of methods may best be conducted by an independent party, but could also be accomplished through the use of a small team of qualified individuals sharing only a desire for progress. NOAA management could also provide more guidance on the purpose and characteristics of the issues and decisions to which scientific methods need to be applied. Such detail could focus efforts toward method selection and development.

The criteria for evaluating alternative population assessment methods must explore more than the scientific qualities of a method. Other factors such as cost, timeliness, and suitability to the decisions at hand are also important. BPA, of course, has done considerable thinking along these lines, and in a paper entitled, "ESA Listings, Jeopardy Standards, Performance Measurement, and the FCRPS (12/22/03)," suggests the following criteria.:

"In considering alternative standards and analytical methods to support listing and consultation decisions, options should be evaluated against criteria to ensure Federal agencies are able to select the most suitable.

1. Timeliness - the method(s) and associated data requirements must be available in a timeframe consistent with the decisions that must be made. These decisions include listings, consultations, and annual performance-based management decisions on allocation of fiscal and operational resources to achieve needed biological results.

2.   "reasonable information standard" - NOAA and USFWS Section 7 regulations require the "…best available data…" to support ESA assessments and decisions, "…regardless of the sufficiency of that data…" Federal agencies are required to do "all that is practicable" to develop information for the consultation. New information needs can be rejected provided such rejection is not arbitrary and capricious.

3.   Cost-effectiveness - Data collection and analytical methods must be cost-effective relative to alternative assessment techniques. Need to consider the annual and long-term costs for collecting the data needed to support the methods. No use adopting complex and expensive methods if the region is ultimately unwilling to pay for it.

4.   Reasonable and prudent – costs for data and assessment methods should be reasonable relative to the fiscal resources available for overall F&W Program administration, M&E, research of critical uncertainties, and investing in actual ESU recovery. Opportunity costs of alternative assessment methods must be considered.

5.   Scientifically Valid - methods must be scientifically valid. Assumptions and uncertainties should be clearly presented.

6.   Value-added – Alternative methods and supporting data requirements should be evaluated based on what additional value they add to the management decisions that need to be made compared to simpler, more cost-effective methods. Do more complex methods add sufficient value to the actual decisions to justify higher costs?

7.   Clarity - methods and analyses must be understandable to Federal decision makers, fishery biologists, elected officials, and key constituent groups.

8.   Currency – analytical methods must be capable of incorporating the most recent years' data in a timely manner.

9.   Parity – analytical methods should only require sufficient precision for the questions that need to be answered, decisions that need to be made (and have been made), and the standards that have been, or will be, established. For example, there is no need to incur high costs for analytical methods that produce precise answers for application to imprecise standards.

10.   Consistency in application – Standards and assessment methods should be consistent and applicable across all arenas of consultation, within and between the 4 H's. For example, including requirements on the FCRPS to ensure viability of an ESU's individual populations should also be then be a requirement for harvest consultations."

We suggest a matrix that compares methods against criteria to ensure complete and objective consideration. We also suggest that some preparation time be devoted to the development of a "common currency" to ensure consistent and equitable treatment of uncertainties and residuals among the techniques.

Application of Methods to Decisions:

Given the dynamic variability of salmon abundance and survival, the variability of available data, their relatively short life cycles, the plasticity of their responses to environmental cues, and abundant adaptive behavior, we can expect substantial uncertainty in the results that Holmes' method, or any other methods may provide. It appears, however, that, even in the face of all that uncertainty, we persist in pursuing a 'secure' analytical method that can instruct a one-time, long-term answer to a set of short-term questions.

ESA decision-making is a series or chain of decisions incorporating the latest information and methodological developments. These decisions are not long lived. Consequently, analytical methods to instruct such decisions should best account for this updating and adjusting to new information on cause-and-effect and population status. Such frequent reviews of information also lead to changes in mitigation actions taken to avoid jeopardy and extinction, and hasten recovery. The current, long-term predictions of extinction risk are, therefore, not only highly uncertain and of questionable use for our predominantly short term decision processes but inherently invalid given the adaptive management built into the ESA decision processes. Over 25, 50, and 100-year periods, a multitude of changes will be made to the habitat and viability of each ESU, and to our basic understanding of the factors that affect an ESU. No method can capture these changes and completely predict the outcomes, although we may gain confidence in our decision making, given a better adapted tool.

Measurement Errors:

The Dennis-Holmes method differs from the Dennis method in that it assumes that some variation in abundance is due to measurement error rather than process error. Clearly, measurement error may be problematic. However, the examples cited (Dunham & Reiman 2000, Jones et al 1998, Hilborn et al 1999) are of very limited relevance for the stocks in question. The first deals with bull trout, a smaller, non-anadromous species which builds redds that are much smaller than those of chinook, steelhead, and coho. The other two address problems with live, transect-style counts (rather than redd or dam counts) of pink salmon spawning aggregates, a physically smaller and far more abundant species than listed salmon and steelhead. The Holmes November 2003 review (p. 9) notes that "[t] he models also include sampling error in the range of that observed for redd-count data (standard error 0.3 to 0.85)", but we can find no cite to sources for these estimates (they do notappear to be in Achord et al 2003).

Conclusion: if examples of measurement error can indeed be found for listed stocks, or at least for the same species of salmonids, it would be very useful to see these in detail in the Diffusion Approximation (DA) methods review. If not, appropriate disclaimers

should be attached to the analyses, to the effect that while measurement error is assumed in the Dennis-Holmes method, we have no empirical estimates of it for the listed species.

Stationarity

A substantial and growing body of literature strongly suggests that cycles in salmonid survival – most likely due to climate effects - are the norm rather than the exception. Furthermore, these climate changes are typically considered to be large, step-function shifts, as opposed to simple autoregressive processes. If this were also the case for listed stocked, this would obviously violate the stationarity assumption of DA methods.

A closely related body of research suggests that one can expect that salmon stocks of the same species, rearing in close proximity, to exhibit strong correlations in abundance, recruits per spawner (R/S), and life-stage survival rates. These correlations are of technical interest because they enable one to use information from large collections of stocks to estimate model parameters. They are also of interest from a management perspective as well; since they strongly imply that the assumption of stock independence made in DA's to date do not hold in practice. Taken together, these would suggest that the failure to discover these relationships with DA methods (e.g., Holmes, "Review of methods …", Figure 7) is limitations of the DA method, and not indications that regime shifts and correlations among stocks do not exist.

Nearly all of these publications either compare multiple stocks with similar spawning locations (e.g., Snake River spring/summer chinook) or aggregates (e.g., all spring chinook spawning above Bonneville Dam), rather than the stock-by-stock approach taken for the majority of DA analyses. In addition, no other analysis that we are aware of that looked for climate effects or multi-stock correlations grouped different species and assumed similar responses to climate, as is the case in Figure 7 (steelhead and chinook). See next two sections for more details and conclusions.

Climate effects

A growing body of literature shows that sharp, step-wise changes in climate are common wherever long-term series of climate indices are available (e.g., Ware, 1995, Beamish et al 1999, Hare and Francis 1994, Downton and Miller 1998). The references merely scratch the surface of a rapidly growing field of study.

A number of recent publications strongly suggest that climate-induced changes in survival rates, R/S, and/or harvest follow step functions. These include Adkinson et al 1996 (BC sockeye R/S), Beamish et al 1999 (BC coho catch), Bradford and Irvine (BC coho R/S), Downton and Miller 1998 (sockeye, pink, and chum catch), Koslow et al 2002 (coho marine survival), Mantua et al 1997 (catch, various spp.), Mueter et al 2002

(*Oncorhynchus* spp. R/S), and Ware and Thompson 1991 (sardine and other spp. catch). All of these publications use either multi-stock R/S approaches (e.g., Adkinson et al 1996, Mueter et al 2002) or use catch aggregated across multiple stocks. We are not aware that anyone to date has detected climate step-function effects in single stocks – the data are simply too noisy to permit such analyses.

However, where data permit it (long time series and R/S having much higher power than short abundance time series), the above discussion suggests we do systematic checks for step functions. Especially for longer time series, harvest estimates should be used to adjust spawning abundance, since rates were much higher pre-1980, the cut-off for most time series in the BiOp. Power and sensitivity analyses for the DA approach would also be useful, to see if climate effects are detectable and evaluate the sensitivity of the DA approach.

Additional Suggestions for Improvements: Multi-stock approaches:

Fortunately, there are many techniques available to model correlations or covariance in stock-specific spawner abundance, R/S, and life-stage survival rates. Botsford and Paulsen (2000) reviews methods for cross-stock correlations on abundance and R/S, and apply these to a number of Columbia basin spring/summer chinook stocks. Paulsen and Hinrichsen (2002) apply R/S regression methods to Snake River spring/summer chinook. Peterman et al (2000) apply Kalman filters to Pacific salmon, while Pyper et al (2002) apply regression methods to chum salmon, and Pyper et al (2001) apply similar methods to pink salmon. Paulsen and Fisher (2001) and Paulsen and Fisher (2003) use regression models applied to multi-stock estimates of juvenile survival. All R/S methods and Paulsen and Fisher (2003) find density-dependent effects in the vast majority of stocks, as well as strong covariation in indicators (abundance, R/S, or survival).

Note that only Botsford and Paulsen (2000) use abundance in their analyses. This suggests that information on age-at-return (for R/S) or life-stage survival rates will be needed for multi-stock modeling, although a recent suggestion used Kalman filters to smooth abundance data to good effect.

Conclusion: multi-stock approaches have done very well at detecting effects that are too subtle for single-stock approaches. Where data permit, different analyses using abundance, R/S, and other metrics over time is recommended to compare stocks and investigate common effects due to climate, hydropower, etc.

Strengthening lambda estimation

The current approach to estimating and characterizing the uncertainty in lambda is to provide separate estimates of stochastic growth rate and sigma^2. Stochastic growth rate is estimated using a running sum approach that uses the same amount of smoothing on each of the data sets to which it is applied. The sigma^2 estimate is calculated using the slope method of Holmes. This approach yields confidence intervals based on a t-distribution with degrees of freedom equal to

$$\text{d.f.} = .333 + 0.212*n - 0.387L \text{ (for } n > 15)$$

where n is the length of the time series and L is the number of counts summed to calculate the running sum (currently 4) (Holmes and Fagan 2002). In the normal i.i.d. case, the degrees of freedom are usually (d.f. = n-1), so it is clear that the current approach presents inefficient estimate of stochastic growth rate in order to reduce the effects of bias. Based on the formula above, in order for the CRI estimates to achieve 20 d.f., 100 spawner observations are needed. In order to achieve just 10 d.f., 53 spawner observations are needed. Using the 22 spawner observations over 1980-2001, which is the current time period for estimating stochastic growth rate, gives us just 4 d.f., which is quite poor. At 4 d.f., the variance of the t distribution is twice as large as it is for 21 d.f. Thus the slope-based method comes at a price: a dramatic loss of precision.

To regain some accuracy in stochastic growth rate while also accounting for measurement error, we would recommend the following:
(1) Combine several populations from an ESU to make inferences about stochastic growth rate. Model selection criteria may support using a single stochastic growth rate for several populations.
(2) Do not treat the populations in (1) as independent. Model the covariability so precision estimate is not inflated.
(3) Choose a method that allows the level of smoothing of the spawner series to change with the estimate of measurement error. High measurement error should increase smoothing which low measurement error should reduce smoothing. As it stand the CRI method uses a high level of smoothing (4 year running sum) for all series.
(4) Check to see if common variances are supported by the data.
(5) Allow for the possibility of stochastic growth rate changing due to different harvest or ocean/climate regime shifts. The current models may be misinterpreting dramatic shifts in vitality rates as part of a noise process rather than nonstationarity.

Kalman filter

The Kalman filter approach presented at the 5 December Llambda workshop can incorporate these suggestions naturally. Lindley (2003) recently applied the Kalman filter approach to model a single salmon population. More generally, a Kalman filter approach applied to multiple stocks is

$$\alpha_t = \alpha_{t-1} + \mu + \eta_t, \quad \text{var}(\eta_t) = Q \text{ (state equation)}$$

$$y_t = \alpha_t + \varepsilon_t, \quad \text{var}(\varepsilon_t) + H \text{ (measurement equation)}$$

where α_t is a $m \times 1$ vector of states, μ is a $m \times 1$ vector of population-specific or common stochastic growth rates, η_t is a multivariate normal noise process with mean 0 and $m \times m$ variance matrix Q, y_t is a $m \times 1$ vector of log(spawner) observations, ε_t is a multivariate normal error term with mean zero and $m \times m$ variance matrix H.

<u>Smoothing</u>. It may be shown that the stock-specific stochastic growth rate estimates are

$$\hat{\mu} = \frac{a_{T|T} - a_{1|T}}{T-1}$$

where T is the number of yearly observations, and $a_{t|T}$ is the smoothed estimate of the state at time t. It is defined as

$$a_{t|T} = E(\alpha_t \mid y_1, y_2, \ldots, y_T)$$

When measurement error in the data increases, the state estimate is based on greater smoothing of the observations. When measurement error is low, the state estimates track the observations closely. Thus, unlike the running sum approach, the level of smoothing used to estimate the stochastic growth rate depends on the measurement error estimate (Figure 1).
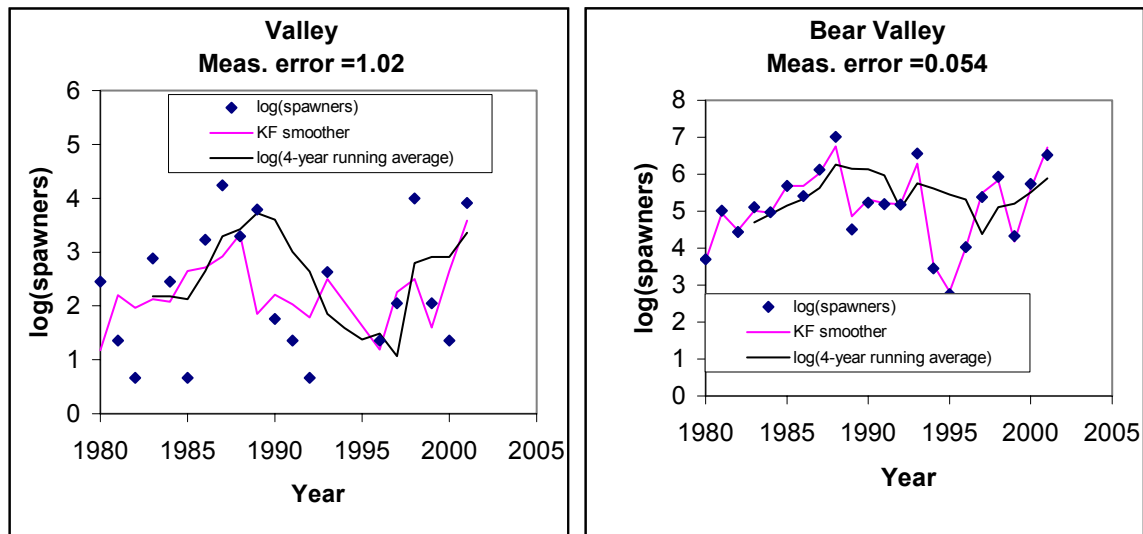

Figure 1. The level of smoothing used by the Kalman filter is greater when measurement error is larger as demonstrated in the above graphs.

<u>Common stochastic growth rate</u>. It is possible to estimate a common stochastic growth rate for the model described above so that all populations have the same stochastic growth rate parameter. This is accomplished by specifying a single parameter in the μ vector. We can then use the likelihood function to calculate AIC and see if the model with a common stochastic growth rate is better supported than the model with stock-specific stochastic growth rates. Preliminary results show that spring/summer chinook index stocks in the Snake River can be combined to increase the accuracy of stochastic growth rate (Table 1).

Table 1. Stochastic growth rate estimates. The model with common stochastic growth rate gives a more precise estimate as indicated by relatively low value of SE (see bolded value). Furthermore, the common stochastic growth rate model has lower AIC. The stock-specific stochastic growth rate model has AIC of 416 while the common stochastic growth rate model has AIC of 407.

Stock	stochastic growth rate	SE	Mean Bias*
Bear Valley and Elk Creek	0.15	0.25	-0.03
Marsh Creek	0.12	0.38	-0.03
Sulphur Creek	0.12	0.42	-0.03
Big Creek	0.12	0.27	-0.02
Lemhi River	0.10	0.19	-0.01
upper Valley Creek	0.11	0.18	-0.03
All (common stochastic growth rate model)	0.19	**0.08**	-0.04

*Mean bias as fraction of SE.

Process error variance bias. The Kalman process error variances tend to be biased downwards, but not to the degree described by Holmes (2003; Figure 3) in the paper "Beyond theory to application and evaluation: diffusion approximations for population viability analysis." Holmes has indicated that the log (process error variances) are not biased in mean, but are highly biased in median. Our analysis shows that the median bias is actually smaller than the mean bias, but that bias is consistently downward. Some bias correction procedure appears to be needed. The largest mean bias was seen in the Lemhi River population which had log (process error variance) that was 50% of standard error (SE).

Table 2. Log(process error variance) estimates from Kalman filter assuming stock-specific stochastic growth rates.

Stock	Log(var estimate)	SE	Mean bias*	Median bias*
Bear Valley and Elk Creek	0.25	0.35	-0.28	-0.25
Marsh Creek	1.07	0.35	-0.28	-0.21
Sulphur Creek	1.28	0.43	-0.30	-0.22
Big Creek	0.37	0.41	-0.27	-0.19
Lemhi River	-0.29	0.48	-0.46	-0.29
upper Valley Creek	-0.44	0.47	-0.21	-0.10

*Bias as fraction of SE.

Correlations. The variance matrix for the process error indicates high correlations among the stocks (Table 3). This suggests that one should not use an estimation procedure that treats the process error of the stocks as independent. Careful consideration of the correlation structure is needed, and the Kalman filter can explicitly model this structure.

Table 3. Process error correlations among stock (Kalman filter estimates). The stock-specific stochastic growth rate model was used.

Bear Valley and Elk Creek	1.00					
Marsh Creek	0.99	1.00				
Sulphur Creek	0.90	0.94	1.00			
Big Creek	0.98	0.95	0.80	1.00		
Lemhi River	0.75	0.78	0.84	0.66	1.00	
upper Valley Creek	0.98	0.97	0.89	0.95	0.86	1.00

Nonstationarity

Because ocean/climate regime shifts and harvest rates can have large effects on stochastic growth rate, it is important to have a modeling framework that can accommodate nonstationarity. One way to deal with this is to explicitly model the nonstationarity using a state space model. One approach would be to rewrite that state equation as

$$\alpha_t = \alpha_{t-1} + \mu_t + \eta_t \quad \text{(state equation)}$$

Where μ_t is a step function described by two parameters (for each population) that can be estimated from the spawner abundance series. If the shift is thought to have a common effect on all of the stocks, that jump in the step function can be estimated as a parameter common to all stocks. As another possibility, if there are enough stocks in the analysis, it may be possible to model the nonstationarity by allowing μ_t to be determined by a series of parameters estimated for every year in the series. In this case,

$$\mu_t = \mu_0 + \theta_t e$$

where μ_0 is a vector representing the mean stochastic growth rate for the populations, θ_t is a scalar series such that $\sum_{t=1}^{T} \theta_t = 0$, and e is a vector of 1s. The various models can be compared based on their AIC scores or some other model selection criteria.

Validation work done by Holmes shows a rather large shift in stochastic growth corresponding to the 1977 regime shift, but indicates that the shift does not reject the null hypothesis of no shift at the 5% significance level. But it must be remembered that changes in harvest scenarios corresponding to changes in population levels can mask the effects of regime shifts. For example, total fishing for ocean and in-river Snake River fall chinook fisheries was reduced by 30 percent or more from pre-listing rates (See http://www.nwr.noaa.gov/1salmon/salmesa/pubs/harvest2.html). This harvest shift took place during the period used for calculating lambdas in the 2000 BiOp (1980-1999). Furthermore, there was no attempt to quantify the power of the test aimed at detecting a regime shift. Regime shifts may be important, but not detectable using the Holmes estimators in the cross-validation test. The Kalman filter approach gives a natural way to

test for a significant shift by directly estimating shifts in the state dynamics. Power to detect important shifts can also be easily quantified, and can be made greater by appropriately combining information from salmon populations in a single model.

Ocean/climate regime shifts

It is becoming increasing apparent that ocean/climate regime shifts play a role in salmon productivity and have a potential to create shifts in stochastic population growth rates that are distinct from a stationary mean noise process. Below, we summarize work on salmon and ocean/climate regime shifts over the last several years.

The National Research Council's Committee on Protection and Management of Pacific Northwest Anadromous Salmonids identified that what happens at sea is important to the conservation and management of Pacific salmon. Interdecadal changes in the ocean environment, especially in water temperature, currents and biological communities, influence the growth and survivals rates, and in turn the returns of adults (National Research Council 1996).

The poor ocean conditions for Columbia River salmon over the last 20 years are in part due to the dramatic decrease in food available for young juvenile entering the ocean. Drops in zooplankton and primary productivity, which feed the salmon food chain, showed a dramatic decrease off the West Coast around 1977, creating a relatively barren ocean environment for West Coast juvenile salmon (Hare et al. 1999).

Ocean/climate regime shifts are signaled by large changes in an index called the Pacific Decadal Oscillation (PDO). In Figure 1, the PDO is illustrated. This is an index that characterizes the month-to-month current patterns, and temperature and sea level pressure distributions in the North Pacific. Researchers have found that positive values of the PDO correspond to a warmer North Pacific and negative values correspond to a cooler ocean (Hare et al. 1999, Mantua et al. 1997).

Most significant is the cyclic nature of the PDO occurring approximately every 20-30 years during the last 100 years. The PDO and other indicators indicate that the North Pacific Ocean suddenly shifted between the warm and cool regimes four times in the past century. Historically these occurred in 1925, 1947 and 1977. The recent PDO information (http://tao.atmos.washington.edu/pdo/) suggests a shift may have occurred in 1998 with the ocean changing from the warm regime that began in 1977 to a cool regime. Recently, Peterson and Schwing (2003) used synchronized shifts in the PDO, zooplankton volumes, coho salmon survival, and biomass anomalies of cold-water copepod species as evidence of a 1998 shift.

The regime after the shift in 1947 favored Columbia River salmon populations, but the shifts after 1925 and 1977 were found to be unfavorable to Columbia River salmon. Besides characterizing the ocean environment, the PDO is also related to streamflow, which affects the ecosystem of salmon in rivers. Streamflow records from British Columbia and Washington State indicate relatively dry conditions during the 1977-1997 period, Mantua et al. (1997) conclude that, "[t]o the extent that high streamflows favor

high survival of juvenile salmon, PDO-related streamflow variations are likely working in concert with the changes to the near-shore marine environment in regard to impacts on salmon production."
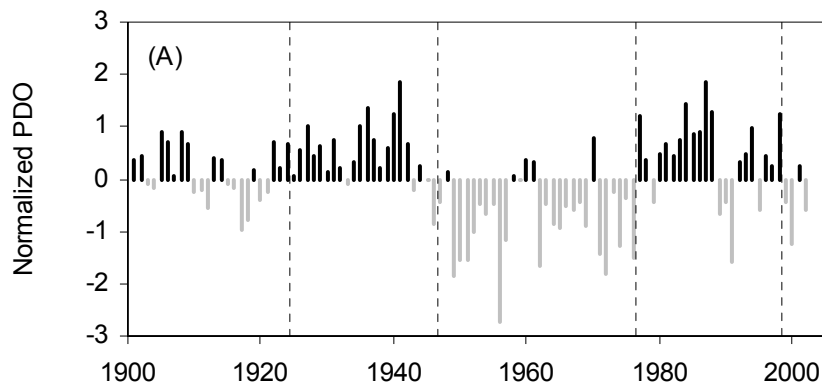

Figure 1. Winter values of the Pacific Decadal Oscillation, an index of sea surface temperature and temperature characterizes the state of the surface waters of North Pacific Ocean. The PDO index shows that the ocean cycles between a warm regime, identified by a positive PDO, and a cool regime, in which the PDO is negative.

Figure 2. Depicted is log (run size) with the mean subtracted, where run size is the estimated number of upriver spring chinook (those that spawn above Bonneville Dam) arriving at the mouth of the Columbia. Data are available from Oregon Department of Fish and Wildlife, (http://www.dfw.state.or.us/odfwhtml/infocntrfish/interfish/crm.html). Positive value bars are black, negative are gray. Dotted vertical lines are drawn to mark the PDO polarity reversal times in 1925, 1947, 1977, and 1998.

Figure 2 illustrates how the abundance of upriver spring chinook has shifted with the PDO. Abundance is expressed as the estimated run size of spring chinook destined to areas upstream of Bonneville Dam. This run includes stocks from the Snake River spring/summer, the Upper Columbia River spring-run chinook ESUs. The data were updated versions of data in Oregon Department of Fish and Wildlife and Washington Department of Fish and Wildlife report (ODFW and WDFW 1999). Notice that run size was above average in the cool ocean regime, below average after the 1977 PDO shift, but returned to above average after the 1998 PDO shift.

The background level used in the 2000 FCRPS BiOp was used to project salmon populations over a century was derived from a period of poor ocean conditions for Columbia River salmon stocks (years 1980 through 1997) (Hare et al. 1999). For most of the past 20 years, ocean/climate conditions have been unfavorable to Columbia River salmon production. Assuming the base period's low background survival rate continues into, and some have hypothesized that ocean conditions may be shifting to a more favorable regime.

The scientific literature contains ample information from peer-reviewed scientific papers that the poor ocean conditions of the 1980s and 1990s are not permanent, and that the climate and ocean experience regime shifts which have large impacts on salmon production (Mantua et al. 1997; Hare et al. 1999). Finney et al. (2000) used sediment records to show that salmon abundance in Bristol Bay and Kodiak Island regions of Alaska have showed market shifts over the past 300 years, and that some pronounced changes appear to be related to climatic changes.

Specific Comments:

Pg. 2: The opening paragraph of the Introduction section sets up the apparent inadequacies of the paper. The purpose of the paper is to review and discuss alternative methods, yet the "… report reviews research since 2000, which tests and validates diffusion approximation methods for estimating population trends and risks." The paper therefore does not fully address the task at hand.

Pg. 4: The discussion of 1) uncertainty and 2) probabilities of crossing thresholds, should consider the life of the decisions (see discussion above) to which the alternative methods are to instruct.

Pg. 7: The paper makes a good, but insufficient effort at explaining the uncertainty that only one critical assumption can make to the Diffusion Approximation Method. In the example, insufficient knowledge about the relative reproductive success of hatchery-origin fish provides a range of 5% to 51% annual growth. This is a 10-fold difference. And as others have pointed out, the relative reproductive success of hatchery-origin fish is likely to be variable between populations, species, spawner density, and through subsequent generations. The paper should more explicitly demonstrate what such an assumption does to analytical results and the predictive capability of this method.

Pg. 13: The statement that long-term population growth rate "… is one of the most commonly used risk metrics within the field of conservation biology" does not appear to comport with our review of methods actually used in ESA recovery plans or in the application of the Species at Risk Act in Canada. More typically, the considerable risk that estimating a distinct rate associated with long term population growth will be encumbered by cyclical or stochastic events unless there is ample knowledge of its component parts, has lead many conservation biologists to use other techniques.

Pg. 17: The discussion here of confidence intervals supports the concern that uncertainty is not evaluated consistently across alternative methods in this paper. Decision makers need to understand the absolute uncertainty associated with results of each method and the relative precision of each method compared to alternative methods. Decision makers can then decide what money, time, and staff effort they want to expend to reduce uncertainty in selection and support of a given analytical method. Decision makers need to also be able to evaluate the scientific validity, including uncertainty, of alternative methods relative to other selection criteria.

Pg. 18: The paper states that the uncertainty associated with calculations using the Diffusion Approximation Method is "… definitely high." The paper needs to more clearly show the uncertainty of long-term predictions from this and all alternative methods. This is an important element for evaluating alternative assessment methods and must be considered within the context of a full suite of evaluation criteria.

Pg. 17-23: A number of potential analytical results are provided that, if accurate, would provide considerable value to decision making. However, the uncertainty surrounding these predictions is not provided. Again, the sum total of the uncertainties associated with key method assumptions (e.g. reproductive success of hatchery fish and data stationarity), short data time series, and data error do not appear to be reflected in the various possible model results presented here. One cannot discern if these output options are just more 'complex, detailed imprecision'.

References

Adkison, M. D., Peterman, R. M., Lapointe, M. F., Gillis, D. M., and J. Korman. 1996. Alternative models of climatic effects on sockeye salmon, *Oncorhynchus nerka*, productivity in Bristol Bay, Alaska, and the Fraser River, British Columbia. Fish Oceanogr. **5**: 137-152.

Adkison, M. D. and R. M. Peterman. 2000. Predictability of Bristol Bay, Alaska, sockeye salmon returns one to four years in the future. North American Journal of Fisheries Management **20**: 69-80.

Beamish, R. J., D. J. Noakes, G. A. McFarlane, L. Klyashtorin, V. V. Ivanov, and V. Kurahov. 1999. The regime concept and natural trends in the production of Pacific salmon. Canadian Journal of Fisheries and Aquatic Sciences **56**: 516-526.

Beamish, R. J., G. A. McFarlane, and R. E. Thomson. 1999. Recent declines in the recreational catch of coho salmon (*Oncorhynchus kisutch*) in the Strait of Georgia are related to climate. Canadian Journal of Fisheries and Aquatic Sciences **56**: 506-515.

Botsford, L. W. and Paulsen, C. M. 2000. Assessing covariability among populations in the presence of intraseries correlation: Columbia River spring-summer chinook salmon (*Oncorhynchus tshawytscha)* stocks. Can. J. Fish. Aquat. Sci. **57**:616-627.

Bradford, M. J. and J. R. Irvine. 2000. Land use, fishing, climate change, and the decline of Thompson River, British Columbia, coho salmon. CJFAS **57**: 13-16.

Coulson, T., Mace, G.M, Hodson, E., and Possingham, H. 2001. The use and abuse of population viability analysis. Trends in Ecology & Evolution. 16(5): 219-221.

Downton, M. W. and K. A. Miller 1998. Relationships between Alaskan salmon catch and North Pacific climate on interannual and interdecadal time scales. CJFAS **55**: 2255-2265.

Hare, S. R. and R. C. Francis. 1994. Climate change and salmon production in the northeast Pacific Ocean, p. 357-372. In R.J. Beamish [ed.] Climate Change and Northern Fish Populations. CJFAS 121.

Finney, B.P., Gregory-Eaves, I. Sweetman, J., M.S.V. Douglas, and J.P. Smol. 2000. Impacts of climate change and fishing on Pacific salmon abundance over the past 300 years. Science, 290:795-798.

Hare, S.R., N.J. Mantua, and R.C. Francis. 1999. Inverse Production Regimes: Alaska and West Coast Pacific Salmon. Fisheries, 24(1):6-14.

Holmes, E.E. 2001. Estimating risk in declining populations with poor data. PNAS 98 (9): 5072-5077.

Holmes and Fagan. 2000. Validating population viability analysis for corrupted data sets. Ecology 83(9):2379-2386.

Koslow, J. A., Hobday, A. J., and G. W. Boehlert. 2002. Climate variability and marine survival of coho salmon (Oncorhynchus kisutch) in the Oregon production area. Fisheries Oceanography 11(2): 65-77.

Lindley, S.T. 2003. Estimation of population growth and extinction parameters from noisy data. Ecological Applications 13(3):806-813.

Mantua, N. J., S. R. Hare, Y. Zhang. 1997. A Pacific Interdecadal Climate Oscillation with Impacts on Salmon Production. Bulletin of the American Meteorological Society, 78:1069-1079.

Mantua, N. J., S. R. Hare, Y. Zhang, J. M. Wallace, and R. C. Francis. 1997. A pacific interdecadal climate oscillation with impacts on salmon production. Bulletin of the American Meteorological Society 78(6): 1069-1079.

Mueter, F. J., Peterman, R. M., and B. J. Pyper. 2002. Opposite effects of ocean temperature on survival rates of 120 stocks of Pacific salmon (Oncorhynchus spp.) in northern and southern areas. CJFAS 59: 456-463.

National Research Council. 1996. Upstream: Salmon and society in the Pacific Northwest. National Academy Press, Washington, D.C.

ODFW and WDFW. 1999. Status Report. Columbia River Fish Runs and Fisheries, 1938-98. Oregon Department of Fish and Wildlife, Clackamas, Oregon.

Paulsen, C.M. and T.R. Fisher. 2001. Statistical relationship between parr-to-smolt survival of Snake River spring-summer chinook salmon and indices of land use. Transactions of the American Fisheries Society 130: 347-358.

Paulsen, C. M. and R. A. Hinrichsen, 2002. Experimental management for Snake River spring/summer chinook (Oncorhynchus tshawytscha): trade-offs between conservation and learning for a threatened species. CJFAS 59: 717-725

Paulsen, C.M. and Fisher, T.R. 2003. Detecting juvenile survival effects of habitat actions: power analysis applied to endangered Snake River spring/summer chinook (Oncorhynchus tshawytscha). Can. J. Fish. Aquat. Sci. 60: 1122-1132

Peterman, R. M., B. J. Pyper, and J. A. Grout. 2000. Comparison of parameter estimation methods for detecting climate-induced changes in productivity of Pacific salmon (Oncorhynchus spp.). CJFAS 57: 181-191.

Peterson, W.T. and Schwing, F.B. 2003. A new climate regime shift in the northeastern pacific ecosystems. Geophysical Research Letters, 30(17), 1896, doi:10.1029/2003GL017528.

Pyper, B. J., F. J. Mueter, and R. M. Peterman. 2002. Spatial covariation in survival rates of Northeast Pacific Chum Salmon. Trans. Am. Fish. Soc. 131: 343-363

Pyper, B. J. et al 2001. Spatial covariation in survival rates of Northeast Pacific pink salmon (Oncorhynchus gorbuscha). CJFAS 58: 1501-1515.

Ware, D. M. 1995. A century and a half of change in the climate of the NE Pacific. Fisheries Oceanography 4(4): 267-277.

Ware, D. M. and R. E. Thomson. 1991. Link between long-term variability in upwelling and fish production in the northeast Pacific Ocean. CJFAS 48: 2296-2306.